Automated Arrhythmia Detection using Hilbert-Huang Transform based Convolutional Neural Network

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Outline

01 Introduction

02 Related work

03 Preliminary

04 Proposed scheme

05 Performance

06 Conclusion

Introduction

1. Being able to diagnosis and classify arrhythmia systematically using machine learning methods is not only convenient and cost effective.

2. Interpreting ECG signals contains nonstationary and nonlinear characteristics.

3. We propose the utilization of Hilbert-Huang Transform due to its adaptive and nonlinear properties.

4. Choose Convolutional Neural Network due to its ability to gain understanding of digital images.

Related work

Conventional Machine Learning Methods

Conventional machine learning methods replies on experts to craft representative features of a given dataset.

1. *Ming-Yuan Li.* proposed a rule-based approach arrhythmia detection on four classes.
2. *Prajwal Shimpi* et al. proposed a method that can classify 13 types of arrhythmia using PCA and bag of words.
3. *MonikaRani* et al. proposed a method that uses SVM to classify three types of heart rhythm.
4. *Hilmy Assodiky* et al. proposed using LSTM to classify arrhythmia with ADaDelta adaptive learning rate method.
5. *Xue Zhou* et al. construct a 4 layered-CNN to classify atrial fibrillation and nonatrial fibrillation rhythm

Related work

Convolutional Neural Network

Convolutional Neural Network has a built-in component capable of extracting features without human interference.

1. *Bahareh Pourbabaee* et al. proposed a patient screening system to improve accuracy. Selecting quality features has the most impact on the outcome of classification or prediction.
2. *Ali Isin* et al. chose AlexNet to implement his arrhythmia classification task on three classes: normal, right bundle branch block , paced beats to improve the robustness of CNN.
3. *Pranav Rajpurkar* et al. built a CNN model layer consists of 34 layers capable of differentiating 12 types of arrhythmia through utilizing a large and representative dataset of 30,000 patients.

Preliminary

Hilbert Huang Transform

Hilbert-Huang Transform(HHT) is an approach for the purpose of analyzing nonlinear and nonstationary data.

1. There are two stages in this method: **Empirical Mode Decomposition**, and **Hilbert Spectral Analysis**.

2. The input signal subtracted by previous IMF (cn) will generate signal rn as the new input signal for sifting, and EMD terminates when no significant frequency can be extracted from rn.

$$x(t) = \sum_{j=1}^{n} c_j + r_n$$

Preliminary

Convolutional Neural Network

Convolutional Neural Network(CNN) is a type of deep neural network that proved effective in image recognition and classification.

1. In the convolutional layer, features from an image will be extracted into maps by performing dot operation of the filters and the raw pixel value.
2. The feature maps will then be applied with a nonlinear function.

3. If the error rate for comparing the prediction to the actual result is high, the values of the filter will self adjust through a series of back propagation until the model has been optimized.

4. The output layer then combined the weighted inputs to produce a scaled result.

Proposed scheme

Data Selection

1. The dataset used in this research is taken from PhysioNet Challenge 2017, AF Classification from a Short Single Lead ECG Recording.

2. We omit the noise class when processing the data as more classes lower the accuracy of overall performance and the noise class itself does not contain useful information regarding arrhythmia detection.

Proposed scheme

Data Overview

The 2017 Challenge dataset is valuable in that it contains data relevant to our goal of classifying three unique classes:

1. **Normal sinus rhythm:**
   Indicator of good health.
2. **Atrial fibrillation:**
   Who may eventually succumb to more serious conditions.
3. **Other rhythm:**
   A variety of unspecified arrhythmia classes.

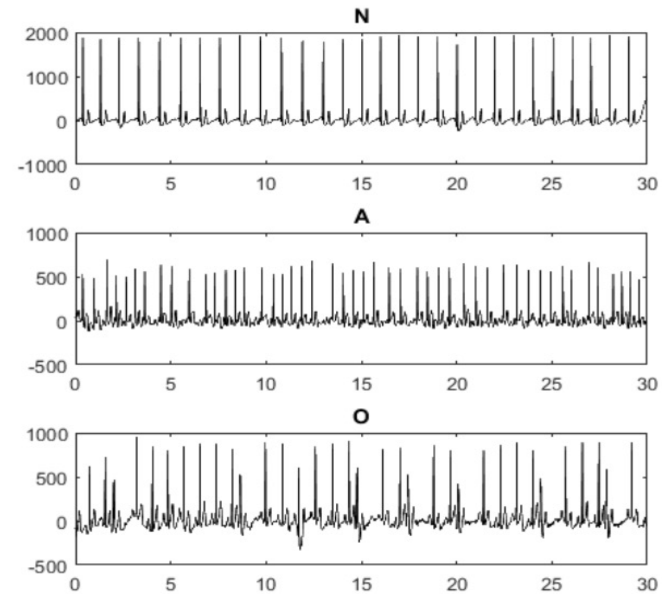


Figure 1: Raw signal of normal sinus rhythm, atrial fibrillation, and other rhythm prior to Hilbert-Huang Transform

Proposed scheme

System Model

We divide the participating components in three parts: preprocessing, HilbertHuang Transform, and Convolutional Neural Network modeling.

Proposed scheme

System Model - Data Preprocessing

The 2017 challenge dataset is a collection of electrical activity of the heart between 9 to 60 seconds.

1. We segment the records into 30 seconds to ensure equal time length.
2. Segments less than a unit requirement will be omitted or truncated.
3. Hilbert-Huang Transform is equipped with noise cancelling properties, simplifying the process.

Proposed scheme

System Model - Hilbert Huang Transform

Empirical Mode Decomposition:

Major component of Hilbert Huang Transform, noise is removed by omitting the first IMF mode for its high oscillation and frequency.

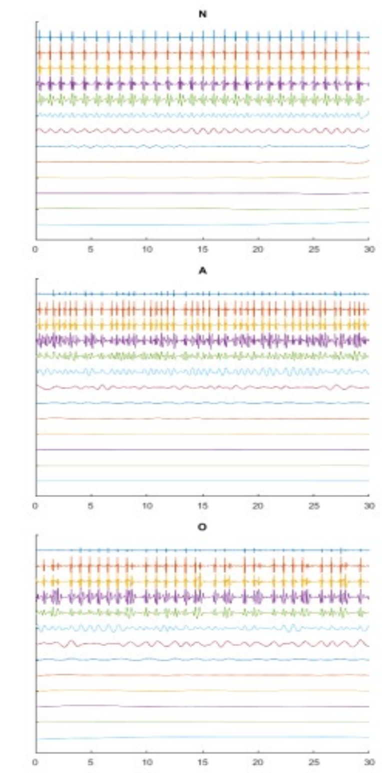


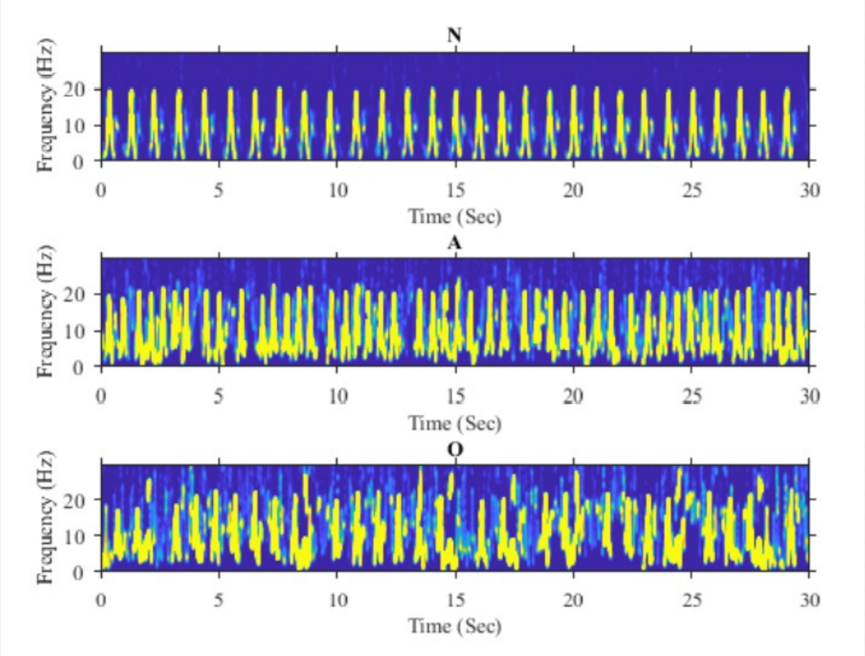
Figure 3: Normal sinus rhythm, atrial fibrillation, and other rhythm after Empirical Mode Decomposition

Proposed scheme

System Model - Hilbert Huang Transform

Hilbert Spectral Analysis:

Hilbert Transform will be applied to the selected IMF modes for all three classes, and the result is shown below.



Hilbert Transformed images of normal sinus rhythm, atrial fibrillation, and other rhythm after signal has been reconstructed using IMF mode 2 and 3.

Proposed scheme

System Model – CNN

Feature Extraction:

1. The input layer, the number of neurons comprising that layer is equal to the dimensions of the raw pixel value of the image.

2. Since images are perceived in 3 dimensions, our network will have 3 convolutional layers and corresponding max pooling layers to ensure distinguishable features from low to high are captured.

3. We set our feature extracting filter to 3x3 filter and our max pooling filter to 2x2.

Proposed scheme

System Model – CNN

Structure	Layer				
	CNN	CNN	CNN	FC	FC
activation	relu	relu	relu	relu	softmax
number of filters	32	64	128	128	3
kernal size	3 x 3	3 x 3	3 x 3	N/A	N/A
pooling	2 x 2	2 x 2	2 x 2	N/A	N/A

Proposed scheme

System Model – CNN

Classification:

1. The fully connected layers will assign a probability of what class the exacted features belongs to.

2. Using the SoftMax operation, the algorithm will then be able to perform multi classification task by assigning the probability of a class between 0 and 1 that adds up to 1.

Performance

Confusion Matrix

	Normal Sinus Rhythm	Atrial Fibrillation	Other Rhythm
Normal Sinus Rhythm	1123	6	121
Atrial Fibrillation	32	87	85
Other Rhythm	99	9	503

We have a total of 2251 samples used for testing, with normal sinus rhythm having 1311 records, atrial fibrillation 329, and other rhythm 611.

Performance

F1 Score

$$PR = \frac{TP}{TP + FP}$$

$$PR_{micro} = \frac{TP_N + TP_A + TP_O}{TP_N + TP_A + TP_O + FP_N + FP_A + FP_O}$$

$$PR_{macro} = \frac{PR_N + PR_A + PR_O}{3}$$

1. Our model overall using micro-F1 yield a 87 percent accuracy while macro yield 86 percent.

2. The F1 score for each class is 90 percent for **normal sinus rhythm**, 87 percent for **atrial fibrillation**, and 80 percent for **other rhythm**.

Conclusion

1. Using Hilbert-Huang Transform to decompose signals of the human body into modes containing temporal information for analysis.

2. CNN to automatically extract features of each class for prediction.

3. Since we were able to distinguished normal, atrial fibrillation, and other rhythm with reasonable accuracy, classifying other classes of arrhythmia should be achievable.

QA Time

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